Environmental Research 161 (2018) 76–86

Contents lists available at ScienceDirect

Environmental Research

journal homepage: www.elsevier.com/locate/envres

Temporal trends in air pollution exposure inequality in Massachusetts

Anna Rosofsky[a,*], Jonathan I. Levy[a], Antonella Zanobetti[b], Patricia Janulewicz[a], M. Patricia Fabian[a]

[a] Department of Environmental Health, Boston University School of Public Health, Boston, MA, USA
[b] Department of Environmental Health, Harvard T.H. Chan School of Public Health, Boston, MA, USA

ARTICLE INFO

Keywords:
Air pollution
Environmental inequality
Environmental justice
Longitudinal analysis
Inequality index

ABSTRACT

Mounting evidence over the past several decades has demonstrated inequitable distribution of pollutants of ambient origin between sociodemographic groups in the United States. Most environmental inequality studies to date are cross-sectional and used proximity-based methods rather than modeled air pollution concentrations, limiting the ability to examine trends over time or the factors that drive exposure inequalities. In this paper, we use 1 km^2 modeled $PM_{2.5}$ and NO_2 concentrations in Massachusetts over an 8-year period and Census demographic data to quantify inequality between sociodemographic groups and to develop a more nuanced understanding of the drivers and trends in longitudinal air pollution inequality. Annual-average population-weighted $PM_{2.5}$ and NO_2 concentrations were highest for urban non-Hispanic black populations (11.8 μg/m^3 in 2003 and 8.4 μg/m^3 in 2010, vs. 11.3 μg/m^3 and 8.1 μg/m^3 for urban non-Hispanic whites) and urban Hispanic populations (15.9 ppb in 2005 and 13.0 ppb in 2010, vs. 13.0 ppb and 10.2 ppb for urban non-Hispanic whites), respectively. While population groups experienced similar absolute decreases in exposure over time, disparities in population-weighted concentrations increased over time when quantified by the Atkinson Index, a relative inequality measure. Exposure inequalities were approximately one order of magnitude greater for NO_2 compared to $PM_{2.5}$, were more pronounced in urban compared to rural geographies, and between racial/ethnic groups compared to income and educational attainment groups. Our results also revealed similar longitudinal $PM_{2.5}$ and NO_2 inequality trends using Census 2000 and Census 2010 data, indicating that spatio-temporal shifts in air pollution may best explain observed trends in inequality. These findings enhance our understanding of factors that contribute to persistent inequalities and underscore the importance of targeted exposure reduction strategies aimed at vulnerable populations and neighborhoods.

1. Background

Ambient exposure to nitrogen dioxide (NO_2) and fine particulate matter ($PM_{2.5}$) have been associated with a range of adverse health effects including increased risk of asthma and respiratory infections (Brauer et al., 2002; O'Connor et al., 2008; Xing et al., 2016), adverse birth outcomes such as early gestational age and low birth weight (Brauer et al., 2008; Stieb et al., 2012; Zheng et al., 2016), increased risk of autism spectrum disorders (Raz et al., 2015; Volk et al., 2013), and all-cause mortality (Franklin et al., 2008; Shi et al., 2016). Mounting evidence over the past several decades has demonstrated inequitable distribution of exposure to $PM_{2.5}$ and NO_2 in the United States among children and older adults, non-Hispanic black and Hispanic populations, low educational attainment and low income populations, potentially contributing to environmental health disparities (Bell and Ebisu, 2012; Brugge et al., 2015; Clark et al., 2014; Morello-Frosch and Lopez, 2006; Su et al., 2009).

However, there are three key limitations in the exposure inequality literature to date. First, much of the environmental inequality (EI) research is cross-sectional, examining environmental inequalities at one point in time. This limits the ability to examine longitudinal trends or the causal mechanisms that drive inequality (Legot et al., 2012; Mohai et al., 2011; Pastor et al., 2004). In particular, there is limited insight about whether disparities are driven by population shifts subsequent to siting of hazardous facilities or roadways, disparate siting practices in poor communities and communities of color, or policies focused on decreasing ambient pollution that simply do not examine distributional consequences. Investigators in both the sociological and environmental health literature argue that residential segregation is a main driver of environmental health disparities (Mohai and Saha, 2015; Morello-Frosch and Lopez, 2006), so demographic shifts over time could have an influence on land use practices, declining social capital and local

* Correspondence to: 715 Albany Street, Talbot Building, T4W, Boston, MA, USA.
E-mail address: arosofsk@bu.edu (A. Rosofsky).

http://dx.doi.org/10.1016/j.envres.2017.10.028
Received 27 May 2017; Received in revised form 13 October 2017; Accepted 17 October 2017

economies and ultimately, community-level environmental exposures (Mohai and Saha, 2015a; Pastor et al., 2004, 2001). Further, demographic change over time could modify inequalities even in the absence of changes in air quality. Therefore, it is imperative to incorporate demographic time trends in air pollution exposure inequality studies.

Second, a limited number of studies have used quantitative metrics to assess EI over space and time. Quantifiable measures of exposure inequality allow regulators to formally assess patterns of EI and to maximize efficiency in exposure reduction policies that seek to reduce environmental exposures, while simultaneously incorporating social equity into distributional assumptions (Boyce et al., 2016; Harper et al., 2013; Levy et al., 2007, 2006). A handful of environmental studies to date have incorporated formal inequality indices to assess geographic and social distribution of environmental hazards (Boyce et al., 2016; Clark et al., 2014; Levy et al., 2007, 2006; Post et al., 2011; Su et al., 2009). These previous studies have adopted welfare-based or health-based measures of inequality to assess sociodemographic distributions of exposure to a single hazard (Boyce et al., 2016; Clark et al., 2014; Fann et al., 2011; Levy et al., 2006; Post et al., 2011) or cumulative environmental hazards (Su et al., 2009). This paper employs the Atkinson Index (AI) (Atkinson, 1970), a relative measure of inequality, discussed in further detail below. Although some previous studies have used the AI to quantify exposure inequality (Clark et al., 2014; Levy et al., 2009, 2006; Post et al., 2011), these studies focused to a greater extent on understanding the inequality implications of air pollution control strategies, and not on longitudinal patterns of inequality.

Most EI studies examine inequitable distributions of hazardous facilities among population subgroups (Mohai and Saha, 2015a, 2015b). A limited, but growing number of EI studies have examined inequalities with respect to both hazardous facilities and traffic-related air pollution using modeled or measured ambient concentrations. However, many are at coarse geographic resolutions, ignore chemical fate and transport and local meteorological conditions, and do not address longitudinal trends in EI (Clark et al., 2014; Hajat et al., 2015; Kravitz-Wirtz et al., 2016; Mohai and Saha, 2015b; Morello-Frosch and Jesdale, 2006; Pope et al., 2016). Pollutants such as NO_2 and $PM_{2.5}$ have significant public health burdens but are not typically dominated by local emissions from hazardous facilities, reinforcing the importance of an exposure-based analytical approach to identify EI occurring at smaller spatial scales.

In this paper, we quantify inequality in modeled ambient $PM_{2.5}$ and NO_2 concentrations between racial, ethnic, income and education groups across Massachusetts between 2003 and 2010 using methods to address the three major limitations in this area of research. The work applies a formal inequality index to examine patterns of exposure among rural and urban populations as a means to identify populations most vulnerable to air pollution exposure within the state. The availability of demographic data from the decennial 2000 and 2010 Census at the block group level and modeled ambient air pollution at a 1 km^2 resolution over an eight-year period provides us the unique opportunity to examine inequalities over time and develop a more nuanced understanding of whether $PM_{2.5}$ and NO_2 exposure inequalities are driven by demographic shifts or longitudinal pollution source distribution.

2. Methods

2.1. Data Sources

2.1.1. Ambient air pollution for Massachusetts, 2003–2010

Daily surface $PM_{2.5}$ at a 1 km^2 resolution was modeled from 2003 to 2010 using a 3-stage statistical modeling approach (Kloog et al., 2014). This modeling approach used a combination of aerosol optical depth (AOD) satellite data retrieved using the multi-angle implementation of atmospheric correction (MAIAC) algorithm, land use and meteorological predictors of variation in surface-$PM_{2.5}$, and monitored $PM_{2.5}$ concentrations (Kloog et al., 2014). This produced an overall "out-of-sample" R^2 for daily values of 0.88, and cross validation results produced a slope of observed versus predicted of 0.99. Details of the $PM_{2.5}$ prediction models can be found in Kloog et al. (2014).

We used daily ground NO_2 concentrations that were estimated for the New England region from 2005 to 2010 at a 1 km^2 resolution from a combination of ground-level NO_2 data at monitoring sites, satellite Ozone Monitoring Instrument NO_2 vertical column density data, and land use regression (Lee and Koutrakis, 2014). Predictors in mixed effects models included population density, distance to major highways, percent developed area, NO_2 source emissions, elevation, and temperature data. This model produced an R^2 of 0.79 and cross validation results produced a slope of observed versus predicted of 0.98, demonstrating high predictive reliability. NO_2 model details can be found in Lee and Koutrakis (2014).

2.1.2. Demographic data

We gathered geographic distributions of race/ethnicity, income, and educational attainment from the US Census and American Community Survey (ACS) at the block group unit of analysis. Measures of educational attainment and income were not collected in the decennial 2010 Census. Therefore, we obtained race/ethnicity data from Census 2010, and measures of income and educational attainment from ACS 2006–2010 5-year estimates. We categorized block groups as rural and urbanized centers according to Census classifications, which rely on population density (Ratcliffe et al., 2016). We utilize Census data at two distinct time periods, 2000 and 2010, rather than at 1-year intervals over the decade under study because the non-decennial 1-year summaries from the ACS are less-reliable, constitute a smaller sample size, and were only collected starting in 2005.

We categorized population characteristics into the following groups:

- Race/ethnicity: individuals in each block group that self-identify as non-Hispanic white, non-Hispanic Black, non-Hispanic Asian, Hispanic or other
- Income: 1999 and 2010 inflation-adjusted median household income as < \$20,000/year, \$20–35,000/year, \$35–50,000/year, \$50–75,000/year, and > \$75,000/year
- Educational Attainment: individuals in each block group ≥ 25 years of age with less than a high school degree, high school graduate, postsecondary degree, bachelors and graduate degree

We aggregated daily $PM_{2.5}$ and NO_2 concentrations to average annual concentrations. Annual $PM_{2.5}$ (years 2003–2010) and NO_2 (years 2005–2010) concentrations were assigned to each block group centroid using the closest 1 km^2 grid cell centroid for each year over the study period. This exposure assignment method was performed separately for Census 2000 and ACS/Census 2010 block groups using ArcGIS 10.3 (ESRI, Inc.).

2.2. Statistical analysis

2.2.1. Summary statistics

We calculated summary statistics for Massachusetts of the number and percentage of individuals and households within each racial/ethnic and education group and the percentage change between 2000 and 2010 stratified by urban (densely developed territories with 50,000 or more people (Census 2000, n = 4277; Census and ACS 2010, n = 4308)) and rural (any territory not defined as urban (Census 2000, n = 654; Census and ACS 2010, n = 596)) block groups (Table 1). Median household income in 2010 dollars is also presented for both time points. Due to the small number of block groups categorized by the Census Bureau as "urban clusters," territories containing between 2500 and 50,000 residents (Census 2000, n = 116; Census and ACS 2010, n = 75), these block groups were excluded from stratified analyses.